EARLY VISUALIZATION APPROACH TO THE GENERATIVE ARCHITECTURAL SIMULATION USING LIGHT ANALYSIS IMAGES

Bomin Kim, Sumin Chae, Youngjin Yoo & Jin-Kook Lee
Dept of Interior Architecture and Built Environment, Yonsei University, Seoul, Republic of Korea

ABSTRACT: *This paper presents the potential utility of generative artificial intelligence-based light analysis simulation visualization image in the early phase of architectural planning and design. Facilitating the simulation of a building's performance during the early stages of planning and design presents numerous advantages, such as cost savings and enhanced ease of communication among stakeholders. However, the assessment of design performance is typically conducted during the design development phase or post-design completion. Processing a substantial volume of data based on design alternatives demands considerable time and resources, thus constraining the immediate provision of simulation results. This paper aims to utilize generative AI to produce visualization results of simulations with a predefined level of accuracy, with a specific focus on the architectural aspect rather than the physical and engineering functionalities of the simulation. Consequently, the study employs the following approach: 1) Analyze prominent characteristics and elements within light analysis simulation. 2) Based on this analysis, generate high-quality visualization image data additionally through Building Information Modeling (BIM). 3) Construct a dataset by pairing the generated lighting analysis visualization image with prompts. 4) Utilize the established dataset to create an additional learning model for light analysis visualization images. This study is expected to provide immediate and efficient assistance in design decision-making during the early phases by generating visualization images with high accuracy, reflecting prominent qualitative aspects related to light analysis and processing within the simulation.*

KEYWORDS: *Architectural Design, Architectural Visualization, Generative AI, BIM (building information modeling), Fine Tuning Model*

1. INTRODUCTION

This study aims to utilize generative artificial intelligence (AI) to create and employ light analysis visualization images within architectural spaces. The current simulation methods quantitatively derive predictive outcomes based on physically designed environmental conditions, which are then visualized. However, as the number of design alternatives increases, processing extensive data incurs time and cost, posing a limitation, particularly in promptly delivering results during the design phase. In the initial design stages, swift generation and evaluation of various design alternatives are vital to meet given requirements. During this process, offering intuitive visualization results rapidly proves more effective than ensuring the precision of simulation outcomes. Therefore, this research is conducted with a primary focus on architectural visualization, which aids in the early design phase, rather than solely relying on physical and engineering-based imagery. In the initial design phase, the precision of the design model is diminished due to the uncertainty of design conditions. However, the utilization of this technology enables straightforward assessment of visual performance aspects, such as a building's energy efficiency and lighting environment, even at the conceptual model level. Particularly, these visualizations serve as effective tools for comparing and evaluating various design alternatives, fostering communication among stakeholders.

Building upon this foundation, a test of the potential for light analysis visualization images in architectural spaces is conducted using image-generating AI. However, the generated images lack reflection of the elements and characteristics of light analysis visualization within spaces, thus clearly indicating the need for further refinement through additional training. For the purpose of generating light analysis images using AI, a process involving '1) Setting the Scope of Light Analysis, 2) Data Preparation, and 3) Training' is carried out. Representative elements of general characteristics from light analysis images are chosen to define the range of training data generation. Model construction employs a diffusion-based model implemented based on the Large Language Model (LLM) for additional training, and hyperparameters are adjusted to ensure the generation of high-resolution images. The constructed supplementary training model is demonstrated in real-world applications of image-generating AI, such as the creation of light analysis visualization images based on different time periods.

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2. BACKGROUNDS

2.1 Image Generation Artificial Intelligence (AI)

The recently emerged generative AI paradigm has entered its preliminary stages, yet it wields substantial influence across diverse industrial sectors. It is anticipated that with ongoing technological advancements, this nascent field will expand the horizons of innovation [Mackinsey, 2023]. Image generative AI such as Stable Diffusion and DALL-E have instigated substantial transformations akin to sectors beyond, including art and entertainment, within the domain of architectural design as well. However, the latent potential within the realm of architectural design visualization remains notably underdeveloped.

This study aims to propose a novel approach to architectural design visualization through the utilization of image generative AI models. Architectural design methodologies intertwined with AI offer a departure from conventional design practices that have traditionally relied upon designers' creativity and expertise to address multifaceted requirements. By systematizing the data generated and incorporated during the design and construction processes through automated tools, the objective is to assist in resolving ambiguities, risks, and other issues that might arise in human-executed tasks by architects, contractors, and related stakeholders.

Given the advancements in LLM models and image generation technologies, the capacity to generate architectural visualization images founded on provided textual input has now materialized. Termed as the process of text-to-image generation, this procedure holds the capability to engender highly realistic images, thereby serving as a multifunctional instrument for the creation of an extensive gamut of architectural visualization content. In light of the continued evolution of AI technology, text-to-image generation is anticipated to assume a pivotal role within the architectural domain. Consequently, image generative AI augments the prospects of creative potential beyond conventional methodologies.

2.2 Potentials of Generative AI on Architectural Visualization

Architectural visualization plays a crucial role in effective communication during the design process due to the intricate nature of design and spatial characteristics [Chiu, 1995]. Notably, architectural visualization techniques such as 3D modeling provide a comprehensive understanding of spatial relationships [Eastman, 1999]. They serve as essential tools for visually expressing complex designs and enabling clear communication with clients and stakeholders. This facilitates the facile comprehension and assessment of project concepts and designs, enabling the early identification of design flaws, leading to cost and time savings and enhancing satisfaction. In the initial stages of design, they prove particularly effective for comparative analysis and review of various design alternatives. Historically, the generation of architectural visualization images required specialized hardware such as GPUs, along with the utilization of dedicated architectural software. This demanded a significant investment of time and effort, ranging from conceptual design configurations to comprehensive design processes. However, with the advent of generative AI, the landscape has transformed. Now, it is possible to efficiently create numerous architectural visualization images with high-performance GPUs, without the necessity for separate platform installations. Through web browsers, one can seamlessly generate highly detailed, high-quality visual images using text-based commands (prompts). This transformation marks a paradigm shift in architectural visualization, affording designers an unprecedented level of efficiency and versatility in the creation and communication of their spatial visions.

3. INTENSIVE TEST USING GENERATIVE AI FOR SPATIAL LIGHT ANALYSIS VISUALIZATON IMAGE

3.1 Image Generation Test for Spatial Light Analysis Visualization Image

In this study, an examination was conducted to assess the feasibility of employing generative AI, utilizing the open-source image generation model "Stable Diffusion" (2022, Stability AI), for the immediate generation of spatial light analysis visualization images. During the testing phase, emphasis was placed on conducting comparative analyses of text-image generation and visualization performance. Furthermore, the scope was delimited to prioritizing visual effects and approximate simulation result visualization, rather than accuracy and precision. While there are two main approaches for AI-assisted image generation, namely, 1) image-to-image (img2img) and 2) text-to-image (txt2img), the latter method of using AI to generate architectural schematics was adopted for testing purposes.

Prompts were formulated under four categories: 1) Scene Description, 2) Geographic Location, 3) Image Quality, and 4) Light Analysis Conditions. The generated images were set to a resolution of 1024x512 pixels. The testing was conducted using the SD model within a local PC environment. A total of 2,000 images were generated through 200 images per testing scenario. On average, it took approximately 5 seconds to generate a single image.

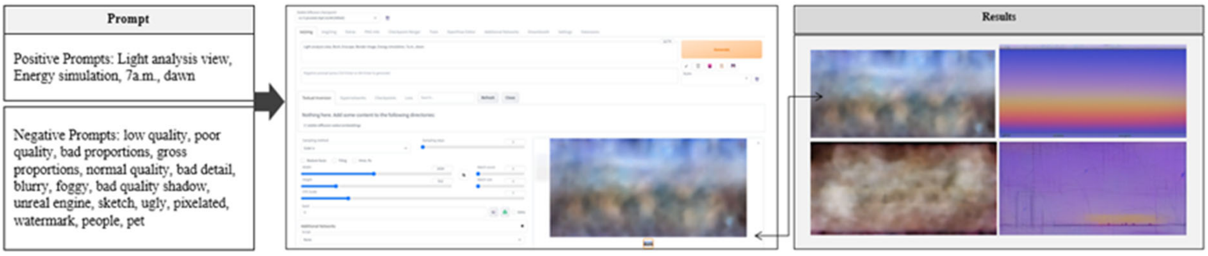


Fig. 1: Procedure for Spatial Light Analysis Visualization Image Generation Test

3.2 Results of Spatial Light Analysis Visualization Image Generation Tests

Based on the results of the previously conducted spatial light analysis simulation visualization tests, the current model has been found unable to generate interior light analysis visualization images of spaces. The lighting simulation visualization images generated through existing image generation models did not exhibit the characteristics of typical simulation images produced using simulation tools, revealing two key issues. Firstly, the model failed to recognize objects composing the space such as windows, ceilings, and walls, as well as lighting fixtures; hence, properties like shading and luminance were not accurately reflected. In essence, these simulation visualizations did not consider the lighting analysis environment. Secondly, there was a lack of consistency in the simulation image outputs, indicative of the absence of defined methods for visualizing quantitative lighting analysis outcomes (view type, visualization style). Consequently, the comparison of design alternatives under uniform conditions became unfeasible. To address these challenges, it is imperative to undergo additional training using lighting analysis images that incorporate the visualization elements and attributes pertinent to lighting simulation. While the existing model proves efficient in generating images across a wide range of domains, enhancing the model's capabilities through additional training is essential for tailored image generation in specific fields due to the constraints posed therein.

4. ADDITIONAL TRAINING FOR VISUALIZING LIGHT ANALYSIS

For the purpose of AI-driven light analysis image generation, an approach involving the following processes: 1) D Definition of the scope of Light Analysis, 2) Data preparation, and 3) Training, is proposed.

4.1 Definition of the scope of Light Analysis

This study focuses on indoor lighting visualization images achievable during the initial stages of interior architecture design through AI methodologies. The light analysis is applicable across the first three stages of design elaboration as outlined in ISO16817 (Project definition – Conceptual design schematic design – Detailed design – Final design). Given that decisions made during the initial design phase significantly influence the subsequent design process direction, preemptively understanding the potential impact of initial design decisions holds paramount importance [Kalay, Y. E. (2004)].

4.2 Data preparation

During the stage of Data Preparation, meticulous consideration was given to the types of training data, the extent of generative scope, and the methods of data creation. Through the utilization of Building Information Modeling (BIM) and rendering techniques for lighting simulation imagery, a process was employed to define the range of light influence elements within the visualization components of lighting simulation, thus facilitating the generation of training data comprising Light Analysis simulation images for indoor spaces.

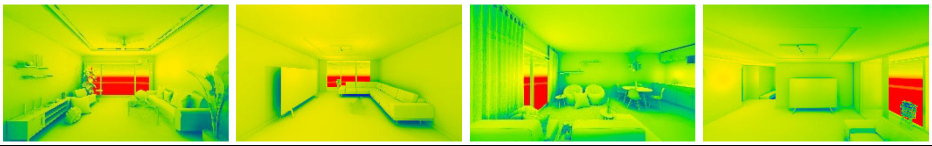
4.2.1 Categorization of Training Data and Scope of Generation

Within the framework of this study, the scope for generating training data was determined based on considerations encompassing spatial design elements, lighting design components, and visualization techniques. Spatial dimensions were confined to the living room, accounting for spatial design elements such as ceilings, floors, walls, and windows (with respective sizes). Lighting design elements were delimited to natural light (primary light source) and specific timeframes (7 a.m., 12 p.m., 6 p.m.), with sunrise at 7 a.m., noon at 12 p.m., and sunset at 6 p.m. The visualization techniques were confined to interior views and photorealistic representations, serving as the basis for generating the training dataset.

4.2.2 Methodology for Generating Training Data and Illustrative Cases

For the process of generating training data, the BIM software named "Revit" was employed to execute interior space (living room) BIM modeling. Subsequent to this, the Revit plug-in program known as "Enscape" was utilized to generate light analysis simulations and rendering images of the modeled interior space. The ensuing outcome images arising from these procedures have been presented in the table indicated by the respective table number.

Table 1: BIM Rendering Image for Additional Training

Training Data Type	Training Data Image
Light analysis view render image_7a.m.	
Light analysis view render image_12p.m.	
Light analysis view render image_6p.m	

4.3 Training

The Additional training was carried out on a local PC equipped with an RTX A6000 GPU model boasting 47.5GB of memory capacity. Two distinct methodologies were employed for additional training: 1) Fine-tuning of the Stable Diffusion (SD) model using the Dreambooth approach, and 2) Training of the SD model using the Low-Rank Adaptation of large Language Models (LoRA) technique. LoRA, a technology employed for image generative AI fine-tuning, facilitates the creation of additional training model files in a brief time frame without necessitating intensive GPU performance. LoRA enables few-shot learning and offers the advantage of promptly and easily observing the impact of styles by altering model file weights. The resultant ". safetensors" LoRA model files, generated upon completion of additional training, can be copied and utilized on other devices.

Fine-tuned models were developed, categorized into cases of fine-tuning the SD model itself and fine-tuning the SD model with the application of LoRA. Each category encompassed three learning types corresponding to different time frames influenced by natural light (7 a.m., 12 p.m., 6 p.m.). Rigorous hyperparameter configuration and combinations were systematically implemented to facilitate precise additional training. Hyperparameter optimization enhanced the quality of generated training model images. The array of hyperparameters considered in this study ranged from image size, batch size, epoch, Caption Extension, learning rate, learning rate scheduler, to learning rate warmup. Given the utilization of LLM-based models for additional training, the process encompassed engineering and pairing image and text (prompt) data. Prompts were classified into Positive prompts and Negative prompts, based on their application status.

Table 2: Configuration Values of Hyperparameters for Additional Training

Model		Training data				Fine tuning hyperparameters
Base Model	Fine-tuned Model	Image type	Number	Prompt text		
				Positive prompt	Negative prompt	

V1-5-puned ckpt	Model 1	Light analysis view render image_7a.m.	10	Light analysis view, Interior image, Revit, Enscape, Render image, Energy simulation, 7a.m., dawn	low quality, poor quality, bad proportions, gross proportions, normal quality, bad detail, blurry, foggy, bad quality shadow, unreal engine, sketch, ugly, pixelated, watermark, people, pet	· Train Batch Size: 2 · Epoch: 150 · Caption Extension: .txt · Learning rate:0.001 · Learning Rate Scheduler: Constant · Learning Rate Warmup:10
	Model 2	Light analysis view render image_12p.m.	10	Light analysis view, Interior image, Revit, Enscape, Render image, Energy simulation, 12p.m., noon		
	Model 3	Light analysis view render image_6p.m	10	Light analysis view, Interior image, Revit, Enscape, Render image, Energy simulation, 6p.m., dusk		

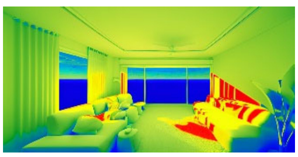
5. OUTPUTS OF ADDITIONAL TRAINED MODEL

Within the realm of AI-driven image generation, two primary approaches exist: 1) Text-to-Image (txt2img), and 2) Image-to-Image (img2img). The txt2img approach generates architectural visualization images based on given textual descriptions. This process demands precision in design due to its sensitivity to factors such as the words utilized, accurate descriptions, and word arrangement. Nonetheless, this approach offers the advantage of efficiently generating realistic images. In contrast, the img2img approach provides the functionality to manipulate and enhance images or photographs, facilitating their reprocessing and utilization. In this section, we aim to demonstrate the outcomes of the trained additional models using both of these image generation approaches, showcasing their capabilities based on the previously conducted additional training.

5.1 Generation of Visualized Images Using the Text-to-Image (txt2img) Approach

To facilitate a comparative analysis between pre and post additional training outcomes, the identical prompts utilized during the preceding intensive test were employed. Prompts were categorized into Positive prompts and Negative prompts based on their application status. Positive prompts were further classified into Scene Description, Geographic Location, Image Quality, and Light Analysis Condition, generating visualization images of spatial light analysis tailored to the characteristics defined by these prompts.

Table 3: Image Generation from Txt2img Approach

Model	Light analysis view render image_7a.m.	Light analysis view render image_12p.m.	Light analysis view render image_6p.m.
Negative prompt	low quality, poor quality, bad proportions, gross proportions, normal quality, bad detail, blurry, foggy, bad quality shadow, unreal engine, sketch, ugly, pixelated, watermark, people, pet		
Positive prompt	Scene Description : Light analysis view, Interior image, Revit, Enscape, Render image, Energy simulation, Livingroom, large window		
	Geographic location (gps location data,country) : 50, Yonsei-ro, Seodaemun-gu, Seoul, Republic of Korea		
	Image quality: low quality, poor quality, bad proportions, gross proportions, normal quality, bad detail, blurry, foggy, bad quality shadow, unreal engine, sketch, ugly, pixelated, watermark, people, pet		
	Light analysis condition: 7a.m. shiny outside	Light analysis condition: 12p.m. shiny outside	Light analysis condition: 6p.m. shiny outside
Output			

5.2 Generation of Visualized Images Using the Image-to-Image (img2img) Approach

Table 4: Image Generation from Img2img Approach

Input	
Prompt	Scene Description : Light analysis view, Interior image, Revit, Enscape, Render image, Energy simulation, Livingroom, large window
	Geographic location: (gps location data,country) 50, Yonsei-ro, Seodaemun-gu, Seoul, Republic of Korea
	Image quality: low quality, poor quality, bad proportions, gross proportions, normal quality, bad detail, blurry, foggy, bad quality shadow, unreal engine, sketch, ugly, pixelated, watermark, people, pet
	Light analysis condition: 12p.m. shiny outside
Output	

6. CONCLUSION

According to the approach proposed in this study, the utilization of Image Generation AI has yielded the capability to generate visualized light analysis images within spatial contexts during the initial design stage, obviating the need for simulation processes. Notably, even at the nascent phase characterized by mere design concepts, the potential for inferring light influx within a space based solely on text descriptions related to these design concepts was evident. This approach has been substantiated by showcasing its capacity to transform not only text but also 3D rendering images into light analysis visualization images. It is worth noting that this study, with its emphasis on visualization from an architectural perspective over a purely engineering one in the light analysis simulation process, may have certain limitations. Nonetheless, this approach harbors the potential to construct models that yield more precise and accurate light analysis outcomes. Particularly focused on the Stable Diffusion model and conducted as an exploratory endeavor into the architectural visualization potential through Image Generation AI at its nascent stages, there lies an opportunity to derive more intricate results through the utilization of diverse generative AI programs and supplementary functionalities. By incorporating these components, the potential for producing even more detailed outcomes is substantial. Furthermore, through the integration of specific requirements of light analysis simulations and domain knowledge-based additional training, there lies the potential for enhancement, affirming the robust potential of Image Generation AI. This study underscores the substantial potential of Image Generation AI by emphasizing its ability to explore the possibilities of architectural visualization.

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